NUTRITION ESTIMATION OF LEFTOVER USING IMPROVED FOOD IMAGE SEGMENTATION AND CONTOUR BASED CALCULATION ALGORITHM

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ABSTRACT

In pandemic conditions, awareness of keeping a healthy balance is necessary. One is considering food consumption and understanding its nutrition content to avert food waste. We have been developing a prototype to estimate the nutrition of leftover food, and the main problem lies in image segmentation. Therefore, we propose the Improved Food Image Segmentation (IFIS) and Contour Based Calculation (CBC) to measure the area of the segmented image instead of pixel-wise. First, the tray box image is acquired and broken down into compartments using an automated cropping algorithm. The first step of this proposed method is tray box image acquisition and dividing the compartment using an automatic cropping algorithm. Then each compartment is treated using IFIS, calculates the result of IFIS by CBC, measures the estimated leftover by Automatic Food Leftover Estimation (AFLE), and then predicts the nutritional content. The evaluation is applied by comparing the actual measurement from the Comstock method and leftover estimation by the proposed algorithm. The result shows that Root Square Means Error (RMSE) reaches 0.48 compared to the actual weighing scale and 96.67% accuracy compared to the Comstock method. Based on the results, the proposed algorithm is sufficient to be applied.

Keywords: *leftover food estimation; food image segmentation; Comstock; nutrition estimation*

1. INTRODUCTION

Understanding the nutritional content of meal consumption during the day becomes essential in this pandemic condition. One way to avoid wasting food is by increasing awareness that leaving food uneaten means wasting its nutritional content. To keep the human body's immune system optimal, people should avoid wasting food behavior. Many researchers have already focused on developing applications to monitor diet (Ciocca *et al.*, 2015; Dehais *et al.*, 2016; Mezgec *et al.*, 2018; Tanuwijaya *et al.*, 2018)

Those applications' fundamental is acknowledging food images using an image processing approach (He *et al.*, 2013; Sari *et al.*, 2020c, 2019b). In this case, we focused on the preprocessing stage, especially for image segmentation acquired in further steps. The determination of the segmented image is the result of the AFLE algorithm. The AFLE is an automatic leftover food estimation in the tray box image (Sari *et al.*, 2019a). Therefore, using this algorithm, we can predict the leftover estimation in a single menu containing several food items in different compartments.

Image segmentation plays a crucial role in producing good detection of food areas in compartments. The result of image segmentation depends heavily on the image's color space. The color transformation is one way to calibrate images already captured using a particular device (Mendoza *et al.*, 2006). Several methods for color transformation on food images are available: HSV and YCbCr, but HSV achieves better results than HSV for food images (Patil *et al.*, 2011). HSV stands for Hue, Saturation, and Value. H represents the type of color described by most wavelengths, S represents the brightness of color, and V represents an image's value. Based on (Singh and Patnaik, 2015), HSV color transformation achieves better performance to handle shadows (Singh and Patnaik, 2015). In this case, it equals the textured background in some compartments of the tray box.

In the previous finding(Sari *et al*., 2020b, 2019a), we were able to determine each compartment's food area in the tray box, as stated before. Therefore, the image segmentation algorithm must be improved since it can deal with the blank compartment problem (Maulana *et al*., 2020). The selection of color channels in a color space produces different segmentation results.

After choosing color channel candidates, a segmentation method divides the foreground from the background. The Otsu segmentation is an algorithm without any parameter to set, classifying pixels into the foreground and background. In the previous research (Sari *et al*., 2017; Sari and Adinugroho, 2018, 2017), the Otsu thresholding was applied to the specific color channel the color spaces achieved a proper image segmentation for tomato images as part of images clustering. This stage is necessary for the preprocessing steps to get the central area of the expected object. This paper proposes enhancing the segmentation quality by combining the S channel from HSV color space to remove the shadow. Several image thresholding methods were combined and tested in the blank compartments, and the result proved that Otsu thresholding is better in the non-blank compartment. Then, the algorithm is called IFIS.

After applying the proposed algorithm for image segmentation, the calculation of the area of segmented image food is utilized. In the preliminary study(Sari *et al*., 2020b), the size of the food image is counted pixel-wise using the AFLE algorithm. AFLE algorithm estimates excess weight in tray box images (Sari *et al*., 2019a). The drawback of pixel-wise estimation occurred when dealing with an insignificant food area. For instance, the pixel-wise assessment calculates the area of a single grain of rice near the ice compartment. The area should be marked as noise since it does not provide significant information for detection. Only the biggest foreground detected is considered as the actual foreground. By doing this, it is expected that the precision of the prediction is increased.

This paper proposes an area estimation of food using a contour-based CBC algorithm. We also improve the IFIS segmentation method by several phases of thresholding. Finally, the weight estimation is handled by the AFLE method. In order to verify the outcome of the proposed method, comparisons with actual weight and observer are managed..

2. RESEARCH METHODOLOGY

The research methodology consists of capturing the primary dataset and cleaning the data. Besides, the detailed steps of nutrition leftover estimation are also calculated, and the evaluation presentation is presented.

2.1 *Taking Primary Dataset*

We focus on leftover estimation, so the number of images of tray boxes containing meals after eating is more significant than before eating. Smartphone camera taken perpendicularly with 30 samples of leftover images dataset and one image of the whole food using a in the uniform lighting condition. A preceding step of taking a picture before and after eating food images is that all food weighs using digital scales. The weighing of each compartment of a tray box is recorded. Then, the weight image before being eaten is used in a different process: the AFLE algorithm. Fig.1 depicts a model when preparing the primary dataset. All images in this manuscript are captured by authors. A single tray box represents a single menu that consists of fried rice *(nasi goreng)*, cucumber (*mentimun*), a blank compartment, and a scrambled egg (*telur dadar*). Table I is an example of the complete data of weighting scales of food before and after being eaten using the digital scales equipment.

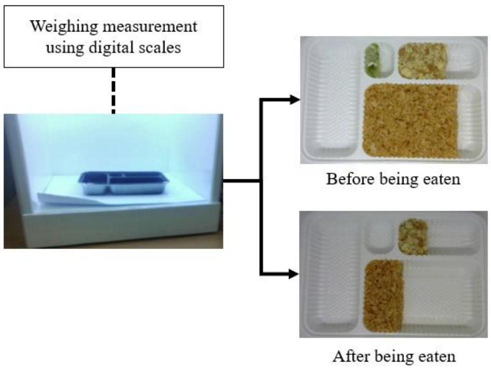
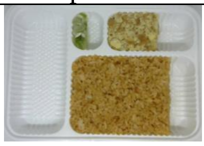


Fig. 1 Preparing Dataset

Table I. Example of Primary Dataset

Weighing measurement (gram (s)) using digital scales	 **Before being eaten**	 **After being eaten**
fried rice *(nasi goreng)*	188 grams	61 grams
cucumber (*mentimun*)	10 grams	0 gram
Blank compartment	0 gram	0 gram
scrammbled egg (*telur dadar*)	38 grams	20 grams

2.1 *Proposed Algorithms*

The whole stage of the proposed method is presented in Fig. 2. The automatic cropping algorithm implements in a previous study (Yuita *et al*., 2020). After that, the improved image segmentation is applied. This paper counts the food image area using the largest contour area from the segmented image. Then, the AFLE algorithm is applied, and nutrition leftover prediction can be identified. The evaluation of weighing and Comstock methods are utilized to ensure that the proposed algorithm is already close to the actual measurement or observer (nutritionist/dietitians) analysis.

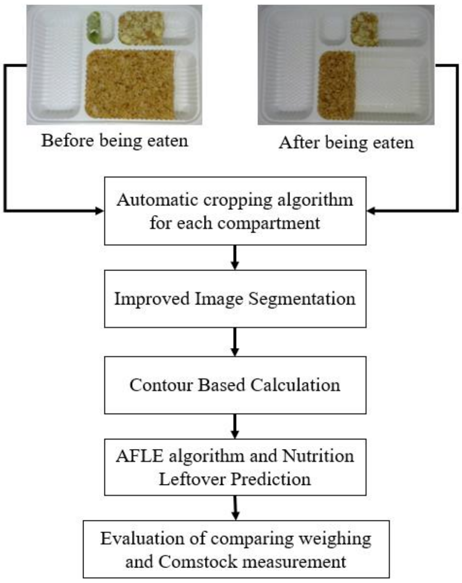


Fig. 2 The whole steps of the proposed method

2.3 *IFIS Algorithms as Food Image Segmentation in Tray Box*

Image segmentation is also necessary for food image analysis (Chavan and Sambare, 2016). IFIS is improved food image thresholding from the previous research (Sari *et al*., 2020b, 2019a). The segmentation problem is near the segmented image's determination resulting in a tray box's blank compartment. This paper focuses on the HSV color channel since this color channel represents the segmented image's projection in different lighting conditions based on our experiment. There are three color channels in HSV, and we put the S color channels due to its result to define the area of food, as stated in Fig. 3. Compared to the H and V color channels, S is clearer to retrieve an image's food area. Then, the whole process of the IFIS algorithm is displayed in Fig. 4 and Fig. 5.

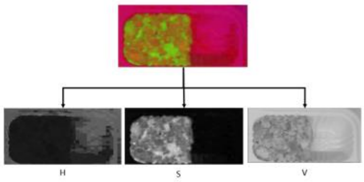


Fig. 3 The HSV color space

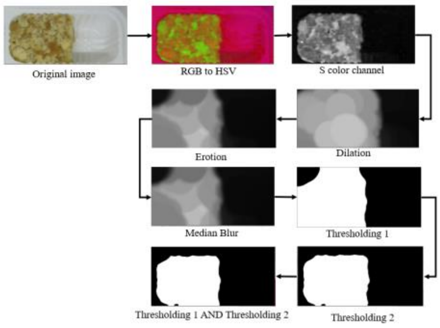


Fig. 4 IFIS in the non-blank compartment

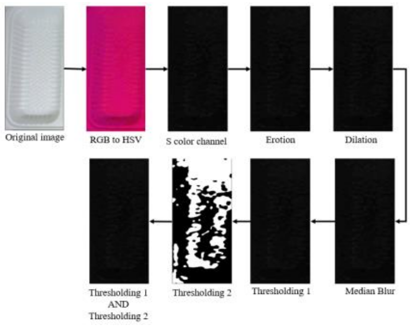


Fig. 4 IFIS in the blank compartment

From the original image, the default RGB color space is transformed into HSV color space

and takes a single color channel representing the primary color's brightness: the S color channel. After that, the dilation and erosion process is applied to get the shape of the compartment's food image area. In this case, we utilize an ellipse as a structured element. Median blur is also applied to enhance the image visualization by decreasing noises among pixels. Further thresholding is challenging since we combine two image segmentation methods that can be applied in the blank compartment. The first thresholding method is focused on tackling the blank compartment problem. We use 90 as a threshold for converting it into a binary image in which the range is 0 and 1, not 0 and 255. The second thresholding is Otsu thresholding, which is automatically treated without tuning the parameter (Harnis *et al.*, 2019).
As depicted in Fig. 4 and Fig. 5, the result of Thresholding 1 is different. In the non-blank compartment, this method is not sufficient to define a food image's food area. On the contrary, the blank compartment achieved perfect results. This condition differs from the Thresholding 2 process; in the non-blank compartment, Otsu thresholding reaches better than Thresholding 1. However, too much noise when it is applied in the blank compartment. So, by concatenating two thresholding processes with those two instances using AND bitwise, it can resolve the problem in both blank or non-blank compartments in plenty of results.

2.4 The *CBC Algorithm for Measuring Area*

The contour-based is applicable for understanding the area of the segmented image (Suzuki, 2017). In the previous method, we apply the number pixel-wise of the segmented image to define an image's area. This paper proposes calculating the segmented area using the largest contour area, as Algorithm 1. The contour is computed in the four compartments in a single tray box.

2.5 *Simple Leftover Estimation (SLE) Algorithm*

This algorithm is suitable almost in the whole case of leftover estimation, involving distinguishing between the area of food image in a pixel or contour with the original measurement. Fig. 6 shows the illustration of predicting leftover food. This method does not count the tray box's original area, so it only compares the initial measurement results to the segmented food image's pixel-wise area. Equation (1) shows the calculation of the estimation of leftover food using the SLE algorithm.

```
Algorithm 1. Contour based calculation algorithms
Input: Cropped image and the result of cropped image segmentation
Output: Drawing contour and find the most generous area
Process:
    1. Find contour from the segmented
       image produced by the IFIS
       algorithm using draw contour.
    2. Calculate the largest contour by
       using a green line as the
       boundary of an item of food
       image.
```

Table II. Example of Contour Based Calculation Results

Before being eaten		After Being Eaten	
Image	**Contour**	**Image**	**Contour**
contour-1 	155099.5	contour-1 	62382.0
contour-2 	8654.5	contour-2 	0
contour-3 	0	contour-3 	0
contour-4 	36982.0	contour-4 	20839.5

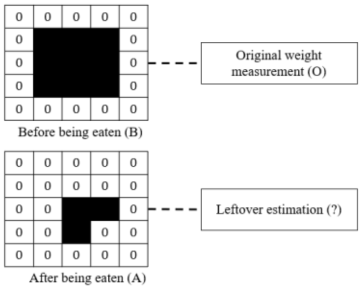


Fig. 6. SLE Algorithm illustration

$$SLE = \frac{O \times A}{B} \quad (1)$$

O is the original measurement using digital scales of food before being eaten. *A* is the pixel-wise or contour base calculation of food after being eaten segmentation, and *B* is the pixel-wise value or contour base calculation for food before being eaten of image segmentation results.

2.6 *Proximate Analysis*

To get the information about nutrition in each food (Aurand *et al.*, 1987), we collect them and analyze them using proximate analysis in the laboratory. We take information on carbohydrates, protein, fat, ash, fiber, water, and fiber. Those nutritional contents represent in grams as unit measurement. Fig. 7 shows the proximate analysis process in the laboratory, and Table III gives information regarding the nutritional content in each part of food items in a tray box per 100 grams. It will be automatically estimated when the leftover food is identified by determining the food weight in the preceding process.

Fig. 7. The proximate analysis in the laboratory

Table III. Nutriotional Contents of Each Food in Tray Box (gram)

Nutrition	*Nasi goreng*	*Mentimun*	*Telur*
Carbohydrate	36,91	3,61	2,61
Protein	3,11	0,86	11,32
Fat	4,25	0,03	29,48
Ash	1,02	0,44	1,22
Water	54,71	95,06	55,37
Fiber	0,16	0,37	0,17

2.7 *AFLE Algorithm and Leftover Nutritional Estimation*

AFLE algorithm is designed to compute the leftover food estimation in a single tray box image that consists of four compartments. Fig. 8 shows the dataset that already cropped automatically into compartments by using an algorithm in the previous finding (Sari *et al.*, 2020a). The AFLE calculation is defined in Equation 2.

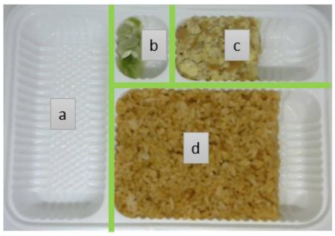


Fig. 8 Cropped each compartment and its label

$$AFLE_i = \frac{\frac{ay_i \times O_i}{ax_i}}{c_i} \quad , \quad i = a, b, c, d \quad (2)$$

where *i* represents the compartment number, which is the detailed explanation illustrated in Fig. 8, *ayi* is the pixel-wise or contour base estimation of segmented result from food image before being eaten, while *axi* is from food image after being eaten. Both *ayi* and *axi* are applying for each compartment of *i*. The variable *Oi* means the original value of digital scale measurements of food before being eaten. Then, *ci* is the constant value of each compartment. In this case, the constant play an essential role in giving the ratio among compartments; the *ci* is valuing is given by Equation (3).

$$c_i = \left[\frac{a_i \times c_d}{a_d}\right] \quad (3)$$

where a_i is the original area of each compartment in which the a_d is the original measurement of the compartment d. In this paper, we apply the tunning parameter of constant c_d that will affect the estimation result, since the compartment shape is not rectangular. So, by putting the constant parameter, it also can adjust the estimation close to the original one.

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After acquiring the value of leftover estimation's food weight, the nutrition calculation in each food item is needed. First, the calculation of the nutritional content of food before being eaten is represented by Equation 4.

$$N_c = \left[\frac{I_c \times w_{bef}}{100}\right] \quad (4)$$

where N_c is nutritional content measurement results for each food item in the food before being eaten, I_c represents nutritional contents from Table III, which is taken from proximate analysis observation, and w_{bef} is actual weight measurement for food weight before being eaten. The N_c result gives the value of the nutritional content of food before being eaten. This calculation is acquired for obtaining the nutrition prediction from leftover food, as stated in Equation 5 and 6 in order.

$$P = \frac{\left|\sum_{i=1}^{k} w_i - \sum_{i=1}^{k} AFLE_i\right|}{\sum_{i=1}^{k} w_i} x100\% \quad (5)$$

where *P* is the percentage value of leftover food from a single tray box, *w* is the original measurement of weight scales of food before being eaten, and *k* is the number of the compartment in a single tray box.

$$P = \sum_{i=1}^{k} Nc_i \times P \quad (6)$$

where *NE* is the nutritional content results from the leftover food in a single tray box, and the *NE* represents the nutritional content of carbohydrate, protein, fat, ash, water, and fiber.

2.8 *Evaluation*

AFLE algorithm is designed to compute the leftover food estimation and the original measurement. How far the prediction or the algorithm is affected by the estimation. We apply Root Mean Square Error (RMSE) (Willmott and Matsuura, 2005) for each tray box of leftover food images, and Equation 7 displays the RMSE value of a single tray box image.

$$RMSE = \sqrt{\frac{\sum_{i=i}^{n}(LE_i \times LO_i)^2}{n}} \quad (7)$$

where *i* is a compartment, and *n* is the number of the compartment in a single tray box. The *LE* value represents the leftover food estimation by algorithm, while *LO* is the original leftover food measurement. The lowest number of RMSE values means that the error is small for the prediction. It means the estimation algorithm achieves good for to be applied.

The RMSE measurement is to compute the distinction between the original weigh measurement and food weight leftover estimation by algorithm, while, to evaluate the comparison between the visual analysis, we apply accuracy measurement for the Comstock value. The Comstock level will be represented by the percentage of total weight measurement in a single tray box. The accuracy (Tharwat, 2021) is presented in Equation 8.

$$Acc = \frac{(k - e_r)}{k} \times 100\% \quad (8)$$

where *k* is the total number of the estimated, and *er* is the number of the dataset does not match between the original Comstock level and the estimation Comstock level. The best accuracy goes to 100%, but near 100% is still remarkable.

3. RESULTS AND DISCUSSIONS

In this part, we divide several experiments to express the result between the weight scale measurement and visual analysis using the Comstock method, which is approached using linear regression. The linear regression gives information on the food leftover estimation level.

3.1. *Leftover estimation using IFIS and CBS Evaluation to the Original Weight Measurement in SLE and AFLE*

We applied two leftover estimation algorithms already described in subsection II from the first experiment. SLE and AFLE algorithms can project the weight of leftover in pixel-wise based calculation and CBC.

The SLE algorithm is the basic algorithm for measuring the leftover based on the ratio between pixels toward the original measurement. However, the AFLE algorithm is designed to compute the leftover food estimation in a tray box image with four compartments. The SLE algorithm can consider being calculated for any case of the container. The AFLE puts its ratio among compartments since the compartment does not precisely have a rectangular shape, so it is more adaptive to handle the leftover weight prediction by defining the cd parameter. In this case, we use cd = 1.1 as a parameter.

Fig. 9 shows that the difference in RMSE between SLE and AFLE is quite significant. In this case, AFLE algorithm achieves better than SLE using pixel-wise based calculation. It has also happened in Fig. 10, where the AFLE is over that SLE for using the CBC algorithm. We apply a pixel-wise approach to count the food image area around the segmented result (Sari *et al.*, 2020b, 2019a). Compared to the CBC algorithm, it can be seen that CBC can decrease the RMSE value more than the pixel-wise algorithm. For instance, in the Fig. 9, for Image5 using the SLE algorithm compared to AFLE algorithm based on pixel-wise calculation reaches 9.00 of RMSE go down until 4.45 of RMSE while using CBC algorithm in Fig 10, it produces 8.91 using the SLE algorithm and dramatically declined to 4.37 using AFLE algorithm. It can be proved that the AFLE and CBC algorithm brings a better result for weight leftover estimation toward the So that, in the next experiment, the result of the CBC algorithm is utilized.

In this observation, AFLE reaches better than SLE, and CBC is better than the pixel-wise calculation for estimating leftover in the tray box. In the previous research (Sari *et al.*, 2020b, 2019a), we conclude that the estimation using the digital image processing approach is affected by segmentation. Before, the segmentation result does not tackle the problem in the blank compartment. Therefore, in this paper, we combined two segmentation processes with two segmentation processes in a sequence: image thresholding and Otsu thresholding afterward.

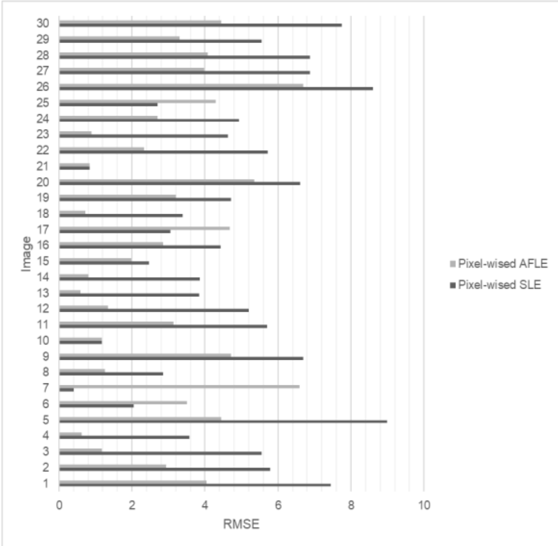

Fig. 9 RMSE using pixel-wise count between AFLE and SLE

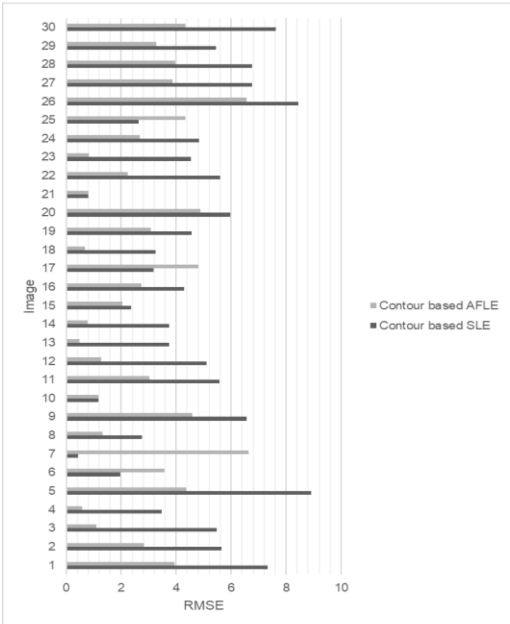

Fig. 10 RMSE using contour-based between AFLE and SLE

As depicted in Fig. 11, Fig 12, and Fig 13, the IFIS algorithm significantly decreased the RMSE value compared to the previous method's segmentation result. The drawback of the primary segmentation method of handling a blank compartment is done using the IFIS algorithm.

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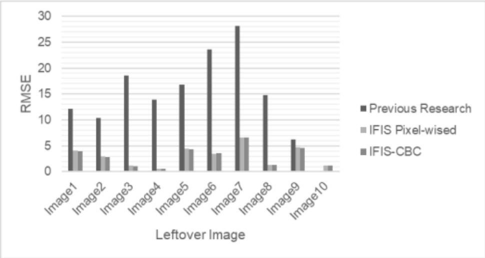

Fig. 11 Comparing RMSE from the proposed method to the previous method (Image1-Image10)

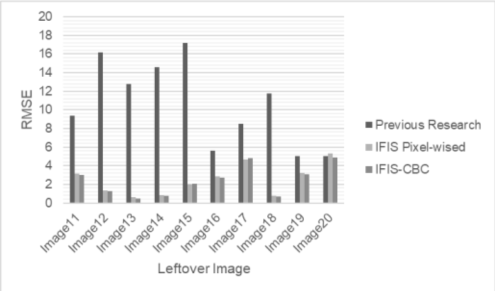

Fig. 12 Comparing RMSE from the proposed method to the previous method (Image11-Image20)

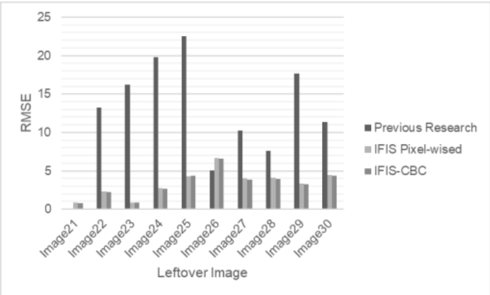

Fig. 13 Comparing RMSE from the proposed method to the previous method (Image21-Image30)

3.2. *Leftover estimation using IFIS and CBS Evaluation to Visual Analysis using Comstock Method with Linear Regression Approach*

Besides comparing to the evaluation using actual weight measurement, the other method to represent visual analysis is using the Comstock level. Comstock gives the level values for a portion of food leftovers. In this paper, we deploy the five levels, which are described in Table IV. The level's label is stated in the right column of Table IV, and the left column is the percentage level of food leftovers, which is already converted into decimal numbers. The 0 level means that there is no remaining food, 1 means 25% of leftovers, two means 50% of leftovers, 3 means 75% of leftovers, 95% of leftovers is represented in level 4, while if the food is still full, then the level of Comstock is going to 5.

Table IV. The Comstock Levels

Comstock level (x)	level (y)
0	0
0,25	1
0,5	2
0,75	3
0,95	4
1	5

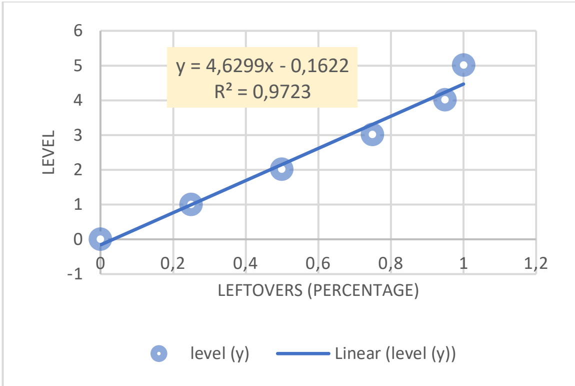

Fig. 14 Comstock modeling using Linear Regression approach

The Linear Regression model is used to estimate the remaining food at the level. The dependent variable is stated in the variable y means the level representation, and the independent variable o fit is in the x as leftovers in percentage unit measurement. Figure 14 shows Comstock's model using Linear Regression, but level 5 does not fit the prediction line. The error of that model is relatively small, which is in the R2 value near 1. The result of the visual analysis is stated in Table VI, where accuracy is going to 96.67% and ends up in Image 5.

3.3. *Nutrition Prediction*

The A and B experiments show that it is already close to the expected estimation. Then, in the nutrition prediction, we use the result of AFLE with IFIS and CBC algorithm to be calculated with the proximate analysis result. Table VI and VII are nutrition predictions before and after eating, respectively.

Table V. The Results of Comstock Levels of The Original Weight and Proposed Methods

Leftovers Image	Comstock Level	
	level (y) = 4,6299x-0,1622	
	Original weight	Proposed method
Image1	3	3
Image2	3	3
Image3	3	3
Image4	3	3
Image5	3	2
Image6	2	2
Image7	2	2
Image8	3	3
Image9	4	4
Image10	4	4
Image11	3	3
Image12	3	3
Image13	3	3
Image14	3	3
Image15	3	3
Image16	4	4
Image17	4	4
Image18	3	3
Image19	4	4
Image20	3	3
Image21	4	4
Image22	3	3
Image23	3	3
Image24	2	2
Image25	2	2
Image26	4	4
Image27	3	3
Image28	3	3
Image29	2	2
Image30	3	3

Table VI. The Nutrition Prediction of Food Before Being Eaten

A menu before being eaten and its nutrition content

Nutrition	***Nasi goreng***	***Mentimun***	***Blank***	***Telur***
Carbohydrate	69,39	0,36	0,00	0,99
Protein	5,85	0,09	0,00	4,30
Fat	7,99	0,00	0,00	11,20
Ash	1,92	0,04	0,00	0,46
Water	102,85	9,51	0,00	21,04
Fiber	0,30	0,04	0,00	0,06

Table VII. The Nutrition Prediction of Food After Being Eaten

A menu after being eaten and its nutrition estimation content

Nutrition	***Nasi goreng***	***Mentimun***	***Blank***	***Telur***
Carbohydrate	50,29	0,00	0,00	0,00
Protein	4,24	0,00	0,00	0,00
Fat	5,79	0,00	0,00	0,00
Ash	1,39	0,00	0,00	0,00
Water	74,54	0,00	0,00	0,00
Fiber	0,22	0,00	0,00	0,00

4. CONCLUSIONS

This paper proposes an enhanced segmentation algorithm by IFIS and CBC algorithm rather than the pixel-wise based calculation algorithm to estimate leftovers' weight using AFLE algorithm. The result shows that the RMSE value between the original weight measurement and the prediction is decreased until 0.48 as the smallest value of error from the whole experiment. Besides, from the visual analysis experiment using the Linear Regression approach, the accuracy reaches 96.67%. It is proved that these proposed algorithms in this paper are applicable to be applied in our prototype: Smart Nutrition Box.

However, we still to improve some algorithms for the next research. For instance, to deal with cropping for cleaning raw data, then improved the leftover estimation if not in the tray box.

5. ACKNOWLEDGMENT

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